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Schematic Maps for Robot Navigation[1]

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Abstract. An approach to high-level interaction with autonomous robots by means of schematic maps is outlined. Schematic maps are knowledge representation structures to encode qualitative spatial information about a physical environment. A scenario is presented in which robots rely on high-level knowledge from perception and instruction to perform navigation tasks in a physical environment. The general problem of formally representing a physical environment for acting in it is discussed. A hybrid approach to knowledge and perception driven navigation is proposed. Different requirements for local and global spatial information are noted. Different types of spatial representations for spatial knowledge are contrasted. The advantages of high-level / low-resolution knowledge are pointed out. Creation and use of schematic maps are discussed. A navigation example is presented.

1 Introduction: A Robot Navigation Scenario

We describe a scenario consisting of an autonomous mobile robot and a structured dynamic spatial environment it lives in. The robot is equipped with rudimentary sensory abilities to recognize the presence as well as certain distinguishing features of obstacles that may obstruct the robot's way during navigation. The robot's task is to move to a given location in the environment.

This task – that appears so easy to humans – is a rather difficult task for autonomous robots. First of all, the robot must determine where to go to reach the target location; thus it needs knowledge about space. Next, the robot must determine what actions to take in order to move where it is supposed to go; thus it needs knowledge about the relation between motor actions and movements and about the relation between movements and spatial locations.

In theory, we could provide the robot with detailed information about the spatial structure of its environment including precise distance and orientation information as well as information about its own location in the environment. The robot then could compute a route through unobstructed space from its current location to the target location. Consequently, some route following procedure could traverse this route.

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In practice, however, this approach does not work. What are the problems? First, it is very hard to provide the robot with detailed knowledge about its spatial environment in such a way that this knowledge actually agrees with the encountered situation in the environment at a given time in all relevant aspects. Even if it agrees, it is impossible to get the robot to carry out actions that correctly reflect the computed result. Second, the real world is inherently dynamic: knowledge about the state of the world at a given time does not guarantee the persistence of that state at a later time.

Why is autonomous robotics so difficult? The general problem a robot must cope with when acting in the real world is much harder than the problem a computer[2] must deal with when solving problems. The reason is that autonomous robots live in two worlds simultaneously while computers only must deal with a single world. Autonomous robots live in the physical world of objects and space and in the abstract world of representation and computation. Worst of all: these two worlds are incommensurable, i.e., there is no theory that can treat both worlds in the same way (Palmer, 1978; Dirlich et al., 1983).

Computers act entirely in a formalized computational (mental) world: their problems are given in formalized form, they compute on the basis of formalized procedures, and the results come out as formal statements. The physical existence and appearance of computers are not essential for the solution of the formal problem. Autonomous robots, on the other hand, are not only superficially submerged in the physical world; they are essential physical parts of their own physical environment. When a robot moves, the physical world changes. In addition to their physical existence, autonomous robots have an important mental facet: autonomous robots are controlled by computers that compute the decisions about the robots' actions in their physical environment.

We can take at least two views regarding the relationship between the physical robot and its controlling computer: (1) We can consider the computer as just a piece of physical circuitry that connects sensor inputs to motor outputs in a more or less complex way. In this view, we do not need to consider representations and mental processes; all issues can be addressed in the physical domain. (2) We acknowledge that formal theories about physical space are required for intelligently acting in a physical environment. Then we have two options: (a) we believe that these theories can be made sufficiently precise to describe all that is needed to perform the actions on the level of the representations; this option corresponds to the classical AI approach. Or (b) we recognize that it is unfeasible to employ a global theory that accounts for all aspects the robot may be confronted with in physical space. Then we can formalize a theory that deals with some aspects of the physical world and leaves other aspects to be dealt with separately – for example in the manner suggested by the first view.

The first view was brought forward most prominently by Brooks (1985). It works well on the level of describing reactive behavior and for modeling adaptation behavior of insects and robots in their environments (Braitenberg, 1984). However, it has not been possible to describe purposeful proactive behavior in this paradigm, so

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[2] We use the term 'computer' to designate the abstract reasoning engine and the term 'robot' to designate a physical device with sensors and effectors that interact with the environment and with a computer that interprets the sensor data and controls the actions.

far. To describe and model intelligent planning behavior, a representation of knowledge about the world is necessary.

In board games or other domains that are defined entirely within a formal framework, a representation with suitable inference procedures is all that is needed to provide appropriate solutions. For tasks and problems that are given in the physical world, however, formal representations must be set in correspondence with the physical world and can only approximate actual situations. This is true not only for robots but also for people and other living beings. Biological systems cope with this general representation problem so well, that the extent of this correspondence problem has been underestimated for a long time. Through the use of robots we have become aware of the severeness of this problem and by using robots we can thoroughly study mappings between the physical world and its mental representation.

An example of information that typically will not be available from a world model is information about an object that happens to have entered the scene due to unpredictable reasons. Another example is the information to which degree a certain location of the robot environment will be slippery and cause a given robot wheel to slip (at a particular angle, at a given force, speed, temperature, etc.). Such situations can be dealt with reactively through perception and adaptation in the environment. In summary, the autonomous robot requires a suitable combination of represented and directly perceived knowledge.

2 A Robot that Communicates by Means of Maps

Our robot is designed to be autonomous to a certain extent: A navigation task is given to the robot and it must find the specified destination autonomously (cf. Röfer, 1999; Musto et al., 1999). Given the situation as described in the previous section, the robot must interact in two directions: (1) it must communicate with the instructor who specifies the task and checks its solution, and (2) it must interact with the environment to master the task. For a human instructor there are three natural modes to communicate spatial information: by deictic means (looking and/or pointing at spatial locations); by a description of spatial locations or objects in natural language; by using a spatial medium to convey spatial information in an analogical manner. Frequently these modes are combined to make use of their respective advantages.

As the robot must interact with its spatial environment to master its navigation task, communication by means of a spatial medium appears particularly advantageous and interesting. Common spatial media to communicate about space are sketches or maps. Maps may serve as interaction interfaces between people and their environment, between robots and their environment, but also between people and robots. In the present paper we explore the communication with robots by means of schematic maps.

The power of maps as representation media for spatial information stems from the strong correspondence between spatial relations in the map and spatial relations in the environment. This allows for reading spatial relations directly off the map that have not explicitly been entered into the representation, without engaging inference processes (Freksa & Barkowsky, 1999). When maps are used to convey spatial information, spatial relations in the map can be directly applied to the environment and vice versa, in many cases. All maps distort spatial relations to some extent, the most obvious distortion being the distortion due to scale transformation (Barkowsky & Freksa, 1997). Most spatial distortions in maps are gradual distortions. No translation of spatial information through symbol interpretation is required as in the case of natural language descriptions.

The strong spatial correspondence between maps and spatial environments has specific advantages when dealing with spatial perception; in our case the robot is equipped with sensors that determine the spatial location of objects to perform its navigation task. The distortions obtained in the sensor readings may share properties with the distortions we get in map representations; thus, the same interpretation mechanisms may be used for the interpretation of the maps and of the sensor readings.

In the setting described, maps can be constructed from the spatial relations in the environment by a human overlooking the environment or by a robot moving through the environment. The human can convey instructions to the robot using maps. In solving its task, the robot can match spatial relations in the map against spatial relations in the environment. And the robot can communicate back to the human instructor by using a map. This provides us with a rich environment to study formal properties of different maps and practical map use. Figure 1 indicates the communication relations between the human and the robot on one hand and the spatial correspondence between the environment and the map on the other hand.

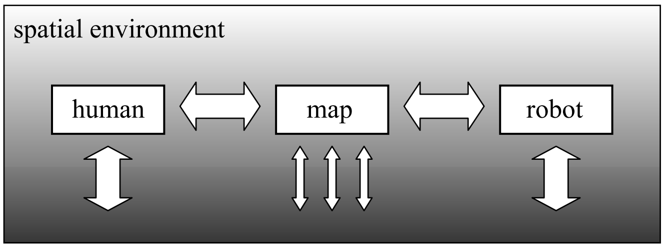

Fig. 1. Spatial communication relations between human, map, robot, and environment (thick arrows). Thin arrows indicate spatial correspondence relations between map and spatial environment

3 Qualitative Spatial Knowledge for Navigation Tasks

Depending on the class of tasks to be performed, different abstractions of spatial knowledge may be useful. To determine what type of knowledge may be most useful to solve navigation tasks, let us consider two extreme cases: (1) the robot knows everything about its spatial environment and (2) the robot knows nothing about its spatial environment. In the first case, the robot does not require perception as it can navigate entirely on the basis of the available knowledge. (We can dismiss this case on the basis of unattainability of complete correct knowledge, in particular in dynamic environments). In the second case, the robot must get all the information to solve its navigation task directly through perception of the environment. (We dismissed this case as unsuitable for developing intelligent navigation strategies.)

Between the two extremes, we should find an appropriate combination of information to be provided externally through the map and information extracted directly from the environment. The information in the environment is superior over information in a map in several respects: (a) it is always correct and (b) it does not require an additional medium. Information provided externally by a map is superior in other respects: (c) it may be available when perception fails (for example at remote locations) and (d) it may be provided at a more suitable level of abstraction for a given task. These considerations suggest that information about the local situation preferably should be obtained directly from the environment through perception while the information about the global spatial situation should be provided externally to allow for developing suitable plans and / or strategies to solve the navigation task.

This division between the primary sources of information also suggests the levels of abstraction the respective information sources should deal with: the information in the environment is very concrete; the perception processes must make it just abstract enough for the decision processes to be able to act on it. The externally provided global information, on the other hand, should preferably be abstract to allow for efficient route planning processes; however, it must be concrete enough to be easily matched to the actual spatial environment.

A suitable level of abstraction for these requirements is the level of qualitative spatial knowledge (Zimmermann & Freksa, 1996). Qualitative spatial knowledge abstracts from the quantitative details of precise distances and angles, but it preserves the information relevant to most spatial decision processes. Navigation then can be carried out in two phases: a coarse planning phase relying mainly on externally provided qualitative global knowledge and a detailed execution phase in which the plan is confronted with the actual details of reality in the local surroundings of the robot (cf. Sogo et al., 1999). This requires that the two sources of knowledge for the robot can be brought into close correspondence.

4 Schematic Maps

Maps to convey spatial relations come in different varieties. Depending on the scale, on the objects to be represented, and on the symbols to be used, they can be more or less veridical with respect to the spatial relations depicted. Scaled-down maps (i.e. in particular all geographic maps) distort spatial relations to a certain degree due to representational constraints (Barkowsky & Freksa, 1997). For many purposes, it is desirable to distort maps beyond the distortions required for representational reasons to omit unnecessary details, to simplify shapes and structures, or to make the maps more readable. This latter type of map we will refer to as ‘schematic map’. Typical examples of schematic maps are public transportation maps like the London underground map or tourist city maps. Both types may severely distort spatial relations like distances or orientations between objects.

Schematic maps are well suited to represent qualitative spatial concepts. The orientation of a line on the map may correspond to a general orientation (or category of orientations) in the nature; a distance on the map may correspond to the number of train stops, rather than to the metric distance in nature, etc. (Berendt et al., 1998).

If we consider abstract mental concepts of the spatial world as constituting one extreme in a hypothetical continuum of representations and the concrete physical reality itself as the other extreme, it is interesting to determine where different types of representations of the world would be located in this continuum. Mental concepts can be manifested most easily by verbal descriptions (in fact, some researchers believe that we cannot think what we cannot express in words - Whorfian hypothesis, Whorf, 1956). When we move in the hypothetical continuum closer to the physical manifestation of the world, we can put concepts of spatial objects and relations into a sketch map to convey selected spatial relations. Sketch maps tend to have close correspondences to verbal descriptions and they are used to augment verbal descriptions by spatial configurations that correspond to spatial configurations in the physical world.

Moving from the other extreme, the physical reality, we obtain a mild abstraction by taking a visual image (e.g. a photograph) that preserves important spatial relations. Moving a few steps further towards concept formation, we may get a topographic map in which objects have been identified and spatial relations from the real environment are maintained. Further abstraction may lead to a schematic map as suggested above. Figure 2 depicts this abstraction scheme.

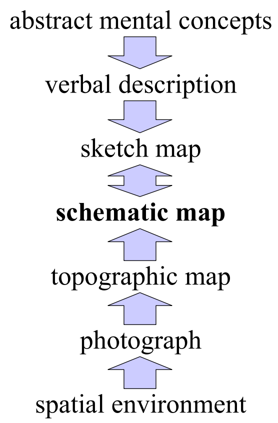

Fig. 2. Abstraction levels between conceptual-linguistic and physical-spatial structures

In this framework, schematic maps differ from sketch maps in that they are derived from topographic maps that are meant to represent a certain part of the environment completely at a given granularity level. Sketch maps, on the other hand, usually correspond to the linear flow of speaking and drawing and frequently to the temporal sequence of route traversal (Habel & Tappe, 1999). Thus, schematic maps provide information about a region while sketch maps more typically provide information about a single route or about a small set of routes. However, there is no sharp boundary between schematic maps and sketch maps as schematic maps may be incomplete and sketch maps may be unusually elaborate.

5 Using Schematic Maps for Robot Instruction

Schematic maps provide suitable means for communicating navigation instructions to robots: they can represent the relevant spatial relationships like neighborhood relations, connectedness of places, location of obstacles, etc. Humans can construct schematic maps rather easily, as the necessary qualitative relations to be encoded are directly accessible to human perception and cognition. But autonomous robots also can construct schematic maps by exploring their environment and by keeping track of notable entities (cf. Fox, 1998; Fox et al., 1999; Thrun, 1998; Thrun et al., 1999); thus, schematic maps can be used for two-way communication between humans and robots.

In Fig. 3 we give a simple example of an initial schematic map of an indoor office environment that may be provided by a human instructor to an autonomous robot. It consists of three rooms, three doors connecting the rooms, and the robot that is located in one of the rooms. This example may serve as reference for the following discussion.

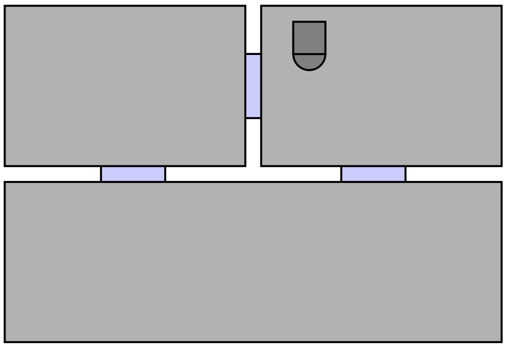

Fig. 3. Schematic map of a simple indoor environment consisting of three rooms, three doorways, and one autonomous robot

Schematic maps can be encoded in terms of qualitative spatial relations. They preserve important ordering information (Schlieder, 1996) for identifying spatial configurations. Qualitative spatial reasoning (Freksa & Röhrig, 1993; Cohn, 1997) can be used to infer relationships needed for solving the navigation task.

To use schematic maps for actual robot navigation, a correspondence between entities and relations in the schematic map and entities and relations in the spatial environment must be established. As we have argued above, this is very difficult to do on the level of high-resolution information. However, we believe that this task can be much more easily performed on coarser, low-resolution information (Zadeh, 1999).

One of the reasons for this is that we can expect a larger number of rare or unique configurations on the coarser and higher level of representation. This should make the approach rather robust against perturbations due to incomplete, imprecise and even partially conflicting knowledge. When spatial relations found in the map and in the spatial environment do not match perfectly, conceptual neighborhood knowledge (Freksa, 1992a, b) can be used to determine appropriate matches.

Furthermore, in realistic settings suitable reference information usually will be available to simplify the problem of matching the map to the environment. Like in route instructions to fellow human beings we can inform a robot about its own location on the map and possibly about its orientation in the environment. Other locations may be indicated by unique landmarks or rare objects that the robot should be able to recognize. These measures help control the number of possible matches between map and environment.

This leads us to the problem of object recognition. Here we adopt a coarse, qualitative approach, as well. Rather than attempting to recognize objects from details in visual images, our strategy is to identify configurations through rather coarse classification and by employing knowledge as to how these configurations may be distorted by the perception and by matching processes. For example, we use coarse color and distance information to identify landmarks in our indoor office scenario. We may relate our approach to Rosch's findings of linguistic categories in human communication (Rosch, 1975). Rosch found that the basic conceptual categories people use in communication tend to be neither the very specific nor the very general categories but intermediate categories that may be most suitable for object identification and concept adaptation.

Multimodal information[3], for example a combination of color, distance, and ordering information, can support the identification process on the level of high-level conceptual entities and structures considerably, as the use of different feature dimensions helps select appropriate matching candidates.

5.1 Creating Schematic Maps

Schematic maps can be created in at least three different ways: (1) by a human observer / instructor; he or she can acquire knowledge about the spatial layout of the environment through inspection and can put down relevant relationships in a schematic map. The actual layout of that map can be supported by a computerized design tool that creates a simple regularly structured map and helps making sure the depicted relations can be interpreted in the intended way; (2) by the robot itself; in its idle time, the robot can explore its environment, note landmarks, and create a schematic map that reflects notable entities and their spatial relationships as discovered from the robot's perspective; (3) from a spatial data base: for artificial environments data about the kinds of objects and their locations may be specified in a data base; this information can be fed into a computerized design tool to create a schematic map, as well.

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[3] We use the term 'multimodal' in a rather general sense. It refers to conceptual as well as to perceptual categories.

5.2 Navigation Planning and Plan Execution using Schematic Maps

The initial schematic map (cp. Fig. 3) provides the robot with survey knowledge about its environment. The robot extracts important features from the map for identification in the environment. The robot can enter discoveries into the map that it made during its own perceptual explorations in the environment. It produces a coarse plan for its route using global knowledge from the map and local knowledge from its own perception. Details of a planning procedure that we use are described in the next section. The resulting plan is a qualitative plan comparable to what people come up with when giving route instructions to a fellow human being: it indicates which roads to take but does not specify in precise quantitative terms where to move on the road.

During plan execution, the robot will change its local environment through locomotion. This enables it to instantiate the coarse plan by taking into account temporary obstacles or other items that may not be present in the map. Also, the local exploration may unveil serious discrepancies between the map and the environment that prevent the instantiation of the plan. In this case, the map can be updated by the newly accumulated knowledge and a revised plan can be generated.

5.3 Communication and Negotiation using Schematic Maps

The robot may not be able to generate a working plan for its task due to incompleteness or incorrectness of the map or due to constraints that lead the robot to believe that it will not be able to move to the destination. Rather than just stopping its actions, the robot should get in touch with its instructor, in such a situation. Using the schematic map, the robot should be able to indicate to the instructor what kind of problem it has in plan generation or plan execution. The human instructor then can inspect the schematic map to evaluate the problem and revise his or her instructions. Figure 4 summarizes the different interaction pathways discussed.

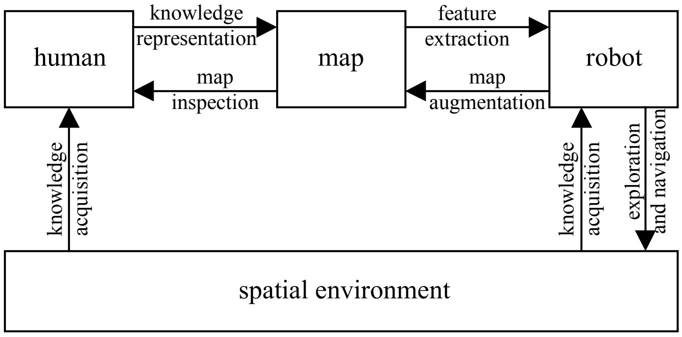

Fig. 4. The interaction pathways between the human instructor, the schematic map, the autonomous robot, and its spatial environment

6 A Simulation Scenario

Currently we develop our scenario such that a simulated robot solves navigation tasks in a simple world with the aid of a schematic map. The schematic map depicts selected spatial aspects of the environment as well as the position and the orientation of the robot and the target location for the navigation task. An example is presented in Fig. 5. The map depicts a few spatial aspects of the three-room office environment in a qualitative manner. Specifically, walls, room corners, and doorways are represented. Other aspects are neglected. For example the thickness of the walls is not depicted. Also, distances and angles need not be to scale, in the depiction.

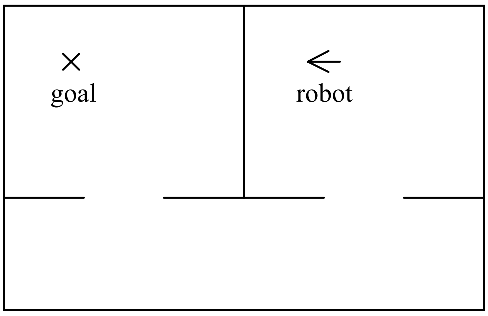

Fig. 5. Schematic map of robot environment including goal location and location and orientation of robot

The sensors of the simulated robot simulate two laser range finders, each covering a range of 180 degrees. Together these sensors yield a panorama view of 360 degrees. Using the schematic map, the robot determines a 'qualitative path', i.e. a path specified only in terms of the route to be taken, not in terms of metrically specified locations. To compute this path the free regions depicted on the map are partitioned into convex regions (Fig. 6a) (Habel et al., 1999).

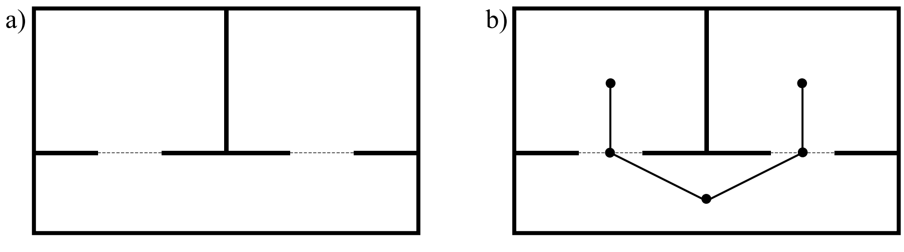

Fig. 6. Qualitative path generation using a schematic map: a) partitioning the free region into three convex cells; b) connecting the cell centers with the centers of their adjacent cell transition lines to obtain the path graph for the route to be traversed

A robot can overlook a convex cell entirely from any location in that cell with a single panorama view. To make use of this feature, the algorithm partitions the free regions in the schematic map into convex cells. Each concave corner is transformed into two convex corners by converting it into a corner of two different regions. A qualitative path graph is constructed by connecting the cell centers with the centers of their adjacent cell transition lines (Fig. 6b). In this graph, the path from start to goal is found by a simple graph search (Wallgrün, 1999).

The simulated robot environment is spatially more veridical than the schematic map. Here, the thickness of the walls is represented and distances and angles reflect the distances and angles of the actual robot environment (Fig. 7).

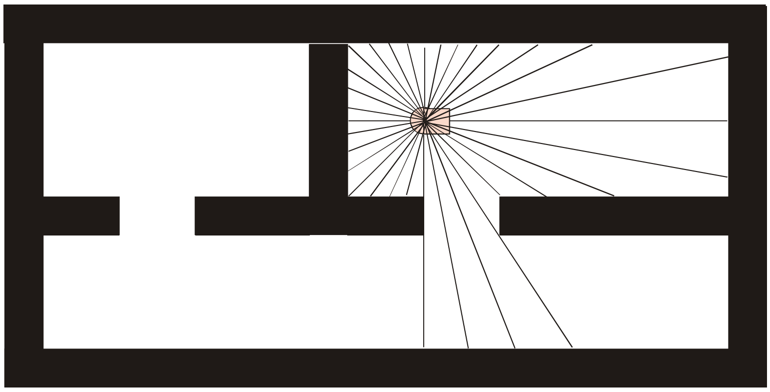

Fig. 7. The simulated robot environment. The spatial dimensions reflect the actual robot environment to scale. The simulated laser range finders measure the distances from the robot to the closest obstacles (walls)

The robot determines a path in the map. Consequently, it will traverse the path in the simulated world. To do this, the robot must establish a correspondence between the schematic map and the world (Fig. 8). This is done by mapping multimodal configurations detected in sensor space to configurations in the schematic map. The mapping task is supported by the use of qualitative spatial relations. This approach promises to be more reliable than isolated feature matching, as high-level feature configurations are less likely to be confused in restricted contexts.

The robot first matches the current sensor percepts with the cell that is marked in the map as its own location (see Fig. 8). The marked cell then is translated into a qualitative spatial representation in terms of vector relative position relations ("double cross calculus" – Fig. 9) (Freksa, 1992b). These relations allow for effective qualitative spatial inferences suitable for wayfinding (Zimmermann & Freksa, 1996). The potential complexity of spatial relationships can be restricted by organizing locations hierarchically (cf. Allen, 1983) and/or by limiting encoding of spatial relations to neighboring entities (Zimmermann, 1995).

Now, the qualitative description of the relevant map area can be matched with the sensor percept produced by the simulation. Since only the qualitative relations are represented the corresponding corners in the simulated world typically have the same relations like the ones on the map. Therefore the correct mapping between the entities on the map and in the world can be identified. Next, the transition line that is on the goal path can be determined in the simulated world. The midpoint of the transition line is the next intermediate goal of the simulated robot. At this point, the neighboring cell is entered, and the new local region is subject of a new map matching process. With this iterative procedure the target location in the simulated environment is reached.

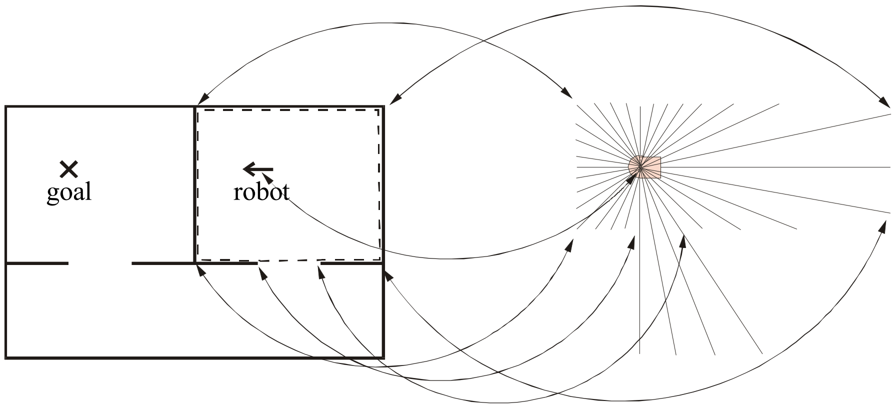

Fig. 8. Correspondence between spatial features in the schematic map (Fig. 5) and spatial features derived from the simulated sensor readings (Fig. 7). The arrows depict the correspondence relations between the corners in the schematic map and those derived from the sensory input, as well as the correspondence relations between the robot's location in the schematic map and that in the simulated world

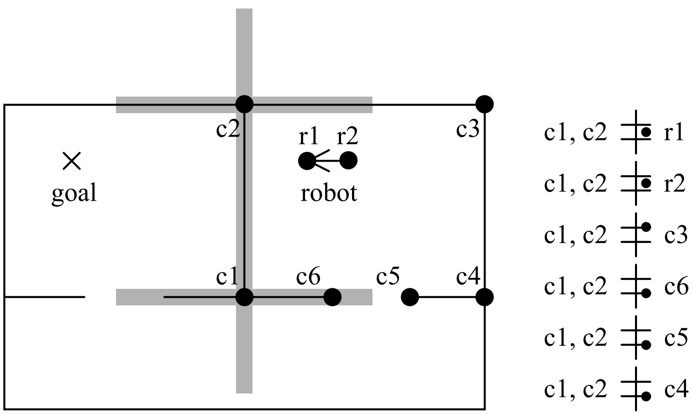

Fig. 9. Spatial relations in local robot region expressed in terms of vector relative position relations suitable for qualitative spatial inferences. Only the relations with reference to the room corners c1 and c2 are presented as an example

7 Conclusion and Outlook

We have presented an approach to high-level interaction between humans and robots on one hand and between robots and their environment on the other hand by means of schematic maps. The approach is based on the presumption that meaningful interaction requires an appropriate level of abstraction for intelligently solving tasks in a given domain. In the domain of wayfinding in a structured environment, a representation of space on the abstraction and granularity levels of decision-relevant entities is considered appropriate. Schematic maps are found to be suitable (1) for representing spatial knowledge on this level, (2) for qualitative spatial reasoning, (3) for human-robot interaction, and (4) for robot-environment interaction.

In pursuing this approach, we proceed in three stages: (1) conceptual design taking into account (a) spatial properties of the perceptual apparatus and the environment, (b) representational tools, and (c) inference methods; (2) implementation and experimentation in a simulation environment emphasizing the spatial reasoning aspects; and (3) implementation in a physical robot environment. The three stages are not carried out in a purely sequential manner; instead we have rather strong interactions between the stages during their development. As the three stages can be developed independently of one another to a large extent, we gain interesting insights about the transitions between the static analytic theory and the dynamic simulation environment on one hand and between the idealized perception / action model in the simulation environment and the real perception / action situation in the physical environment, on the other hand.

The work we are reporting on is work in progress. We have developed a formal system for qualitative spatial reasoning, a platform for simulation studies for spatial reasoning, and we have carried out experiments in physical robot navigation on the basis of qualitative spatial knowledge. The main focus of our present work is on the simulation environment that we build on the basis of our existing qualitative spatial reasoning theories. In parallel, we carry out perception studies in the physical robot environment to determine the type of landmarks we can use best for the navigation task.

In our future work on this project we will particularly focus on issues of dealing with incomplete sensor and map information, exploiting neighborhood and other spatial structures, matching descriptions of different granularity, and integrating information sources of different modality. We plan to experiment in our simulation environment successively with additional features and modalities to better understand and reduce the gap between the simulation and real environments.

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